Managed Care, Drug Benefits and Mortality: An Analysis of the Elderly

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Abstract:

We seek to investigate whether managed health care can affect mortality, and if so, through which mechanisms. We estimate the impact of Medicare+Choice (M+C), Medicare's managed care program, on elderly mortality, using a county-level panel from 1993 to 2000. We control for endogenous M+C penetration rates with county fixed effects and instrumental variables. We construct instruments using the identification created by the fact that M+C payment rates are based on 3– to 8–year lagged fee-for-service (FFS) costs in the county. We find that enrollment in managed care without prescription drug coverage significantly increases mortality while enrollment in managed care with drug coverage has no significant impact, both relative to FFS. The impact of managed care penetration on mortality from heart disease appears to follow a similar pattern. The estimates suggest that a 10-percentage point increase in M+C non-drug coverage would cause 51,000 additional deaths among the aged population in 2000.

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1: Introduction

In 2000, 15% or over 6 million Medicare enrollees bypassed the traditional fee-for-service (FFS) program and enrolled in a managed health care plan through the "Medicare+Choice" (M+C) program. The M+C program generally provides access to more health plan benefits — the most desirable of which is prescription drug coverage — at the potential cost of having health care utilization managed. In this paper, we seek to understand the impact of managed care and drug coverage on health outcomes for the elderly.

Understanding the role of managed health care in affecting the health of Medicare enrollees is germane for several reasons. First, both academics and recent legislation (e.g. Dowd, Feldman and Christianson, 1996 and the Medicare Prescription Drug, Improvement and Modernization Act (hereafter the Medicare Drug Act) of 2003) proscribe moving the Medicare program towards privately administered health plans and our work can shed some light on the impact of such a change on health care quality. Second, the M+C program is directly affected by policy levers available to the Congress and the Centers for Medicare and Medicaid Services (CMS), the administrative agency that oversees the Medicare program, such as payment rates and regulations, and our work can help understand the mortality consequences of past and potential future policy changes. Finally, over the 1990s managed care has come to dominate the private health insurance market in the United States and it is important to understand how this dramatic shift impacts health outcomes. Our work may shed additional light on this issue.

The most valuable optional M+C benefit is prescription drug coverage (Town and Liu, 2003). This benefit has become increasingly important during the 1980s and 1990s with the development of many new and expensive drug therapies (Lichtenberg, 2002a and 2002b). This increasing importance together with the fact that many Medicare enrollees do not have drug

coverage[1] led the government to enact the Medicare Drug Act of 2003. Under this legislation, Medicare enrollees will obtain prescription drug benefits through private Prescription Drug Plans or Medicare HMOs. Government subsidies for prescription drug insurance may increase welfare by lessening the adverse selection inherent in private health insurance, but the effect of managed care on the health of the elderly is unknown.

In this paper, we examine the impact of M+C penetration rates with and without drug coverage on mortality rates at the county level. Ideally, we would identify the impact of managed care penetration by using a source of experimental variation in the penetration rates. However, the major health insurance experiment – the RAND experiment – predates both the rise of managed care (Manning et al. 1987) and the important wave of pharmaceutical introductions of the 1980s and 1990s.[2] Without such variation, managed care penetration rates are likely endogenous, as people are likely to select into managed care and drug coverage based on their underlying health status and health plan entry decisions may be based, in part, on the health status of potential enrollees. In this case, a regression of mortality on managed care penetration rates will yield inconsistent estimates of the true treatment effects. Moreover, because of the complex nature of patient and provider selection, it is difficult to even try to sign the bias in the coefficients.

The literature on the impact of managed care penetration on health outcomes has not reached any consistent conclusions, perhaps in part because of the endogeneity problem. A review by Miller and Luft (2002) reports that over the period 1997-2001, 9 studies find that HMOs lead to lower mortality, 12 find that HMOs lead to higher mortality, and 6 find no

[1] In 1999, 38% of Medicare enrollees did not have drug coverage (Laschober et al. 2002).
[2] Furthermore, we are unaware of any published results from the Health Insurance Experiment on the sensitivity of prescription drug use and outcomes.

difference. Three papers on the M+C program (Maciejewski et al. (2001) and Riley et al. (1989, 1991)) find that HMO enrollees have a lower probability of death than other Medicare enrollees. However, some recent studies find no significant difference between M+C and Medicare FFS for breast cancer, prostate cancer, end-stage renal dialysis, and acute myocardial infarction.[3]

In contrast to this literature, we control for the endogenous managed care penetration rates by exploiting a very useful source of quasi-experimental variation for this managed care program, which is the M+C payment rates. To understand our method of identification, it is useful to outline the specification. We postulate that the elderly mortality rate in a county is a function of the drug- and non-drug managed care penetration rates (with FFS as the omitted category), as well as observed county health status and a residual health shock. We control for county health status by including county fixed effects as well as socioeconomic status (SES), other forms of health coverage such as Medicaid, and regional trends. The managed care penetration rate is endogenous because enrollment decisions and plan entry are correlated with the unobserved health shock.

The M+C payment rate was based on the mean of the 3– to 8–year lag of realized, per-capita FFS expenditures in the county. Our method creates instruments from the M+C payment rate, and hence will identify the impact of managed care on health outcomes based on the impact of an increase in the M+C payment rate on the elderly mortality rate. To satisfy exogeneity, the payment rate must be uncorrelated with the unobserved shock, which is the component of mortality that remains after controlling for the county fixed effects and other observables as well as the endogenous treatment into managed care. A high, unobserved health shock is certain to raise health care costs and hence raise the payment rate. However, the increase in the payment

[3] See Lee-Feldstein et al. (2000), Roetzheim et al. (2000), Potosky et al. (1999), Eggars et al. (2002) and Sada et al.

rate will only occur three years hence. Thus, the payment rate can be an appropriate instrument if the residual health shock at time t is uncorrelated with the residual health shock at time t+3. Since we control for a broad variety of observable health factors, including county fixed effects, this is a reasonable assumption, and also one for which we bring some empirical evidence to bear. We report results from a forward mean differenced estimator that controls for fixed effects and the fact that the instruments are uncorrelated with the contemporaneous regressor but not strictly exogenous as well as from standard fixed effects instrumental variables estimation.

We use a sample of approximately 460 large counties with 70% of the U.S. population for which mortality data is publicly available. Because we separately examine the impact of drug and non-drug coverage, we have two endogenous variables. Thus, we create several instruments from the M+C payment rate, based on the generosity of the payment rate relative to similar counties. We chose these instruments to try to span the determinants of profits that are likely to influence firms entry and plan offerings decisions.

We find that an increase in the enrollment in M+C plans without prescription drug coverage is associated with a significant increase in elderly mortality (p-value = .01). However, we find no significant differences between enrollment in M+C plans with prescription drug coverage and non-M+C elderly mortality. Using our base estimates, a 10 percentage point increase in the non-drug M+C enrollment coming from either drug M+C or Medicare FFS would increase the elderly mortality rate by .15 percentage points, or by 2.9 percent, corresponding to approximately 51,000 additional deaths in 2000.[4] Using a value of $100,000 per life year, the economic value of these lives is approximately $5.1 billion or $1,500 per additional non-drug

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(1998).

[4] The 95% confidence interval is 14,400 to 86,600 lives.

M+C enrollee.[5] These results are fairly robust across a variety of different specifications, and also occur for mortality from heart disease. However, we find no significant link between M+C penetration rates and mortality from cancer or for 50 to 59 year olds.

The remainder of this paper is divided as follows. Section 2 provides a background on the institutional framework. Section 3 presents the model. Section 4 presents the data. Section 5 presents the results. Section 6 concludes.

II. Background

In 1982, Congress passed the Tax Equity and Fiscal Responsibility Act (TEFRA) which directed the Health Care Financing Administration (HCFA), now called the Centers for Medicare and Medicaid Services (CMS) to contract with health maintenance organizations (HMOs) to provide a managed care option to Medicare enrollees. Under Medicare+Choice (M+C), the current name for the program, Medicare enrollees can choose to forgo the traditional, fee-for-service (FFS) Medicare insurance program and enroll in a qualified HMO. In exchange for a per-capita payment from CMS, the HMO provides, and is at risk for, all FFS Medicare-covered services (Parts A and B) for the enrollee.

HMOs offer M+C plans by county on an annual basis, agreeing to accept all Medicare enrollees with the given county of residence.[6] HMOs can provide benefits beyond FFS coverage including (but not limited to) prescription drugs, eye care, dental coverage and preventive care and can charge a non-zero premium to their enrollees, both subject to CMS approval.[7]

We focus on the Medicare program for the aged, which serves 35 million of the 41

[5]This figure can be compared with the $674 average drug expenditure for Medicare enrollees (Poisal and Chulis, 2000).
[6] More precisely, for a given M+C contract, HMOs submit proposed service areas,, which are clusters of counties in a given locale, to CMS for approval.

million Medicare enrollees. Each year from 1982 until 1997, HCFA set the per-capita M+C payment at 95% of its projected cost (Parts A + B) to treat a similar enrollee in the FFS program. The per-capita payment is the sum of a county/year-specific base payment for the aged and an increment based on age, gender, and Medicaid and institutional statuses. Until 1997, the projected cost was the mean Medicare FFS claims for that county, for the period from eight to three years prior.

In 1997, President Clinton signed the Balanced Budget Act (BBA). The BBA (and its subsequent modifications) fundamentally modified Medicare's payment methodology.[8] While the changes in the payment formula are rather technical, for our purposes the important feature of the new payment formula is that updates to the county payments were eventually divorced from the Medicare FFS experience in the county.[9] The post-BBA payment formula led to a substantial decrease in payment rates in most counties. The new Medicare Drug Act of 2003 significantly increases the payments to Medicare HMOs, particularly those who offer drug coverage, in order to encourage greater enrollment in M+C plans.[10]

In counties where the M+C option is available, Medicare beneficiaries can choose to enroll or disenroll in an HMO on a monthly basis. If the beneficiary is not in M+C, she is automatically enrolled into Part A of the FFS program. Part A covers hospital stays (with a small deductible) and catastrophic care. In addition, FFS enrollees can (and mostly do) enroll in Part B for a premium (in 1998 that was $43.80 per month). Part B covers physician services with a 20% coinsurance; lab and diagnostic tests; outpatient services with a 20% co-payment and mental

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[7] Currently, CMS is allowing Medicare HMOs to charge negative premiums to enrollees. Over our sample period, the minimum premium a plan could charge was zero.
[8] With the passage of the BBA, the Medicare HMO program also received its current name: "Medicare+Choice."

health care with a 50% co-payment. Not covered in Medicare's Part A and B program are long-term care, prescription drugs, preventive care, dental care, and eye care.

Most Medicare FFS enrollees (92%) also have supplemental insurance that offers additional benefits above Parts A and B. This supplemental insurance is either individually purchased, or provided by the government (through Medicaid, Veterans Affairs, or State Pharmaceutical Assistance) or employer. Often this coverage provides prescription drug benefits. In 1995, of the non-M+C Medicare beneficiaries, 13% also had Medicaid (which provided drug coverage to 90% of this group), 35% had employer sponsored Medigap insurance (86% with drug coverage), 31% purchased Medigap in the individual market (46% with drug coverage), 3% had other government sponsored coverage (80% with drug coverage) and 9% have a mixture of coverage (80% with drug coverage).[11]

III. Model

We seek to determine the impact of drug and non-drug M+C coverage on elderly mortality. Using county level panel data, we examine the probability of elderly mortality in county i at time t. Our basic model expresses:

$$(1)\quad m_{it} = \alpha_i + \delta_t + \gamma_d d_{it} + \gamma_{nd} nd_{it} + \beta x_{it} + \varepsilon_{it}$$

where m_{it} is the elderly mortality rate, α_i are fixed effects that control for county health status, δ_t are annual dummies that control for medical advances, nd_{it} measures the percent of elderly

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[9] From 1998 onwards, the rates are the set to the maximum of three rates: blended input price—an adjusted national rate and an area-specific rate; a floor payment designed to increase the rates in low-paying counties; and a minimum rate increase of 2% per year.

[10] Under this legislation Medicare+Choice will receive a new name: Medicare Advantage.

people enrolled in an M+C plan without drug coverage, d_{it} measures the percent enrolled in an M+C plan with drug coverage, x_{it} measures time-varying county health status and health coverage characteristics, ε_{it} indicates unobserved shocks to health status, and the γ s and βs are parameters. We include in x_{it} variables that capture time-varying components of the socio-economic status (SES) of the county, including the percentage of people of each age, racial composition, mean per-capita income and unemployment rate.[12]

We also need to capture any time-varying county-specific component of the non-M+C health coverage for the elderly. In 1996, 69% of Medicare beneficiaries had drug coverage,[13] principally through Medicaid, M+C plans, and supplemental Medigap coverage. Thus, we include the percent of elderly Medicaid enrollees in some specifications. We also would like to include the availability of supplemental Medigap coverage. It would be problematic to include the Medigap quantity, because these data are not available and may be endogenous even if they were available. As a proxy for availability, we include Medigap prices in some specifications.

Our principal interest is in estimating γ_{nd} and γ_{d}, the impacts of non-drug and drug M+C enrollment on mortality, respectively. Note that plans may offer benefits (e.g. lower co-pays, broader provider network, and dental care) other than drug coverage that are potentially correlated with drug coverage. While we believe that drug coverage is the most important benefit, we cannot rule out the possibility that drug coverage proxies for these other benefits.

The omitted category in our analysis is FFS Medicare. This category is made up of individuals enrolled in a variety of insurance schemes from Medicaid to individually purchased

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[11] Source: Davis et al. (1999).

[12] This specification assumes that managed care enrollment affects contemporaneous mortality. We explored using specifications that allowed for managed care enrollment to have a lagged effect on mortality and the coefficients on lagged enrollment were small and insignificant.

Medigap coverage to no supplemental coverage. 37% of this population does not have prescription drug coverage.

Ideally, we would like to observe variation in the health coverage for elderly people that is exogenous conditional on the county fixed effects and other county observables. Unfortunately, we are not aware of a source of exogenous variation. However, the Medicare payment rates form a useful source of quasi-experimental variation. We proceed by discussing the endogenous enrollment decision and illustrating how that decision process leads naturally to instruments based on the payment rates.

The decision by a Medicare enrollee of whether and which type of M+C plan to join, and hence the M+C penetration rates, will be related to the prevalence of M+C managed care plans in the county as well as to health status. Town and Liu (2003) find that M+C penetration is increasing in the CMS payment rate. There are likely two underlying causes. Increased variety means that more patients find an M+C plan that is close in product space and increased competition leads to lower prices and higher quality. It is possible that less healthy Medicare recipients may choose not to join managed care plans, because of the limitation of the choice of physicians. However, it is also possible that Medicare recipients may join M+C plans, particularly those with drug coverage, because they will then pay for less of the costs of medical treatment. Thus, the bias in γ_d and γ_{nd} from endogeneity could go in either direction.

The decision of a managed care plan to enter into the M+C market is likely to be driven by the health status of the population as well as by the Medicare payment rates.[14] Moreover, health plans will be more likely to offer drug coverage if M+C offers relatively generous

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[13] See Poisal and Chulis (2000).
[14] Ellis and Gurol (2002) find substantial entry and exit of health plans from the M+C market resulting from changes in the payment rate.

payment rates in the county. Last, because of the fixed costs of entry and exit, health plans may choose to enter, and to standardize benefits, across counties in a metropolitan area. Thus, the health plan entry and exit decisions are likely to cause a further endogeneity bias in the managed care penetration rates nd_{it} and d_{it}.

We use an instrumental variables (IV) approach to control for the fact that the M+C penetration rates nd_{it} and d_{it} may be correlated with the residual health status ε_{it}. Our approach is to use functions of the payment rate as instruments.[15] Prior to 1998, the payment rates were based on the 3– to 8–year lagged mean health care costs in that county. Although there is only one payment rate per county, we need a minimum of two instruments as we have two endogenous variables. Because offering, entry and enrollment decisions are a complex function of the payment rate, there is plenty of available variation to identify these two parameters. The difficulty is in extracting from the payment rate the quasi-experimental variation caused by events such as a random healthcare shock three years prior that would then affect these decisions.

In a given year we use 13 instruments $z_{it} \equiv \left(z_{it1},...,z_{it12}\right)$ instead of 2, to improve efficiency. We first normalize the payment rate based on population, by regressing the payment rate on four measures of population (county population, health services area (HSA) population, MSA population and county elderly population), and using the residual from this regression as the normalized payment rate. We then use 10 instruments based on the normalized payment rate: the rate, its second, third and fourth powers its log and the square of its log, and 4 dummies indicating its quintile (with one excluded). We also use 3 instruments that indicate the mean, minimum and maximum payment rates in the MSA, to capture the cost complementarities noted above. We normalize our instruments by population and nearby payment rates because

population is a good predictor of costs. Thus, these instruments will capture shocks that affect margins, which in turn will affect entry, offering and enrollment decisions.

The z_{it} s will be good instruments if they meet three conditions. First, that they are strong predictors of the vector of managed care penetration rates nd_{it} and d_{it} after controlling for explanatory variables x_{it} and the county fixed effects. Second, that they are properly excluded from the mortality equation (1). And third, that they are uncorrelated with the unobserved shocks to health status ε_{it}. We discuss each of these points in turn.

First, our model of health plan entry and Medicare enrollees' choice implies that the instruments are related to the M+C market shares. Moreover, as noted above, Town and Liu (2003) have found that the payment rates are very good predictors of the M+C market shares as average plan quality is increasing in the payment rate. Because of the randomness of the health shocks, there is substantial within-county variation in the payment rates and the payment rates are still very good predictors, conditional on x_{it} and fixed effects. In order to determine the power of the instruments, we perform first-stage regressions of the endogenous regressors nd_{it} and d_{it} on the instruments z_{it}, the exogenous regressors x_{it}, and the fixed effects, as suggested by Bound, Jaeger and Baker (1995). The tests show that the instruments are strong predictors. We can strongly reject the null hypothesis that they do not enter in these regressions, with $F(36;3,497)= 2.21$ ($p=.00$) for nd_{it} and $F(36;3,032)= 11.10$ ($p=.00$) for d_{it}. The appendix presents the results of the two first-stage regressions.

We also jointly estimated the same two equations with a SUR model, in order to test whether the coefficients are the same across the two equations. The test strongly rejects the

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[15] Our payment variable is the base payment rate for each county.

coefficients being the same with $\chi^2(100) = 1{,}322$ (p=.00). This implies that the first-stage projections of the endogenous variables, which we can write as $\widehat{nd}_{it}$ and $\hat{d}_{it}$, are significantly different from each other, which is necessary to separately identify the treatment effects of drug and non-drug managed care coverage on mortality.

Second, the instruments can be properly excluded from the mortality equation (1) if functions of the payment rate are not direct predictors of health status after controlling for the county fixed effects, M+C penetration rates nd_{it} and d_{it}, and regressors x_{it}. It is worth considering an example of when z_{it} might enter directly into the elderly mortality equation. Suppose that high payment rates attract high quality physicians to an area. This may then lower mortality for all elderly patients, not just those enrolled in M+C. However, this example is very unlikely because of the presence of the county fixed effects. Specifically, it is unlikely that physicians would move to an area because of transitory payment changes, and permanent differences in compensation will be captured by the fixed effects in (1). Hence, we think that it is reasonable to exclude z_{it} from (1).

Last, we need to understand whether z_{it} is correlated with the unobserved shocks to health status ε_{it}. This assumption is not directly testable. We would expect that z_{it} is correlated with the lagged residual health statuses, $\varepsilon_{t-8},\ldots,\varepsilon_{t-3}$, since an increase in costs is likely to accompany an increase in the mortality rate.[16] Thus, the most likely source of correlation between z_{it} and ε_{it} is a positive serial correlation between ε_{t-3} and ε_t. While we cannot directly test for the presence of this correlation, we can bring some evidence to bear by examining the

[16] See Fuchs, McClellan and Skinner (2001).

correlation between the residuals from a reduced-form regression. Hence, we perform a reduced form fixed effects regression of:

(2) $m_{it} = \delta_i + \phi_1 x_{it} + \phi_2 z_{it} + u_{it}$,

with a within-county AR(1) process for u_{it}, so that $\text{Corr}(u_{it}, u_{it-1}) = \rho$. We estimate an AR(1) coefficient of $\rho = .14$, which implies that the estimated correlation between u_t and u_{t-3} is $\rho^3 = .0027$. This does not seem consistent with a sizeable, positive serial correlation between ε_{t-3} and ε_t. Thus, it appears that the payment rates are based on sufficiently lagged payment histories that they are not correlated with the contemporaneous residual health status.

We perform our estimation using linear IV estimation, with county-level fixed effects. As a potential robustness check, we estimate a weighted IV estimator that accounts for the fact that the mortality rates in larger counties are based on more observations. The results from the weighted regressions are very similar to the unweighted regressions so we do not report them here.[17]

A potential problem with our method of inference is that our instruments are not strictly exogenous. While we assume that z_{it} is uncorrelated with ε_{it}, it is likely correlated with ε_{it-3}, due to the mechanism by which the payment rates are set. In panel data instrumental variables models, if the panel is too short to achieve consistency in the time series dimension, then strict exogeneity is required for consistency.

To see this, note that fixed effects IV estimates are equivalent to estimates from a mean-differenced instrumental variables specification. For ease of notation, let us assume that our dataset extends from $t = 1, \ldots, T$. Then, the dependent variable can be written as $m_{it} - \frac{1}{T}\sum_{s=1}^{T} m_{is}$,

and other variables can be expressed similarly. As ε_{it} may be correlated with z_{it+3}, this will induce a correlation between the instrument $z_{it} - \frac{1}{T}\sum_{s=1}^{T} z_{is}$ and the residual $\varepsilon_{it} - \frac{1}{T}\sum_{s=1}^{T} \varepsilon_{is}$ in a short panel, due to the $\frac{1}{T}\sum_{s=1}^{T} z_{is}$ and $\frac{1}{T}\sum_{s=1}^{T} \varepsilon_{is}$ components of these random variables. However, if the panel is sufficiently long, then shocks to ε_{it} will have little impact on $\frac{1}{T}\sum_{s=1}^{T} \varepsilon_{is}$, and this will not be problematic.

With 8 years of data, this correlation may be problematic, but is unlikely to have a major influence on the estimates. Nonetheless, we develop a forward mean differenced specification that is robust to this potential correlation. For this specification, we subtract the mean from $t-1$ to T for every time-varying variable in (1); thus our dependent variable is:

$$(3) \qquad m_{it} - \frac{1}{T - \min\{1, t-1\} + 1} \sum_{s=\min\{1,t-1\}}^{T} m_{is} .$$

We then include as instruments z_{it-1}, z_{it} and z_{it+1}, using zeros for cases when $t-1<1$ or $t+1>T$.[18] Absent serial correlation, only z_{is} for $s \geq t+2$ will be correlated with our resulting error term, $\varepsilon_{it} - \frac{1}{T - \min\{1, t-1\} + 1} \sum_{s=\min\{1,t-1\}}^{T} \varepsilon_{is}$, and thus this specification encapsulates county fixed effects and solves the correlation problem caused by the absence of strictly exogenous instruments. In Section 5, we mostly present results from the forward mean differenced fixed

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[17] The results of these regression are available from the authors upon request.

[18] There are several possibilities of exact choices of instruments. Asymptotic efficiency dictates including every z_{is} for $s \leq t+1$. For a similar specification, Arellano and Bond (1991) suggest including each of the available instruments, but Keane and Runkle (1992) suggest a smaller set of instruments because of the possibility of substantial bias in finite samples.

effects IV specification, but also present some results from a standard fixed effects IV estimator for comparison purposes.

IV. Data

Out study period is 1993-2000. We choose 1993 as the start of the sample as prior to this year enrollment in Medicare HMOs was very small. We create a county-level panel data set of mortality rates and other county-specific information. The data come from seven different sources that are merged together. First, the mortality data is constructed using the Multiple Cause of Death data from the National Vitality Statistics. These data contain abstracted death certificate information including the county of residence, age, sex, and diagnosed cause of death for all deaths in the US. To ensure confidentiality, the county is listed only for those individuals who reside in a county of over 100,000 in population. Thus, we limit our sample to counties above this population threshold.

Second, we merge the mortality data with county level data from CMS on M+C plan enrollments, plan prescription drug benefits, total Medicare enrollment, and the M+C constant dollar payment rate. We define the drug benefit using the base plan as reported by CMS.[19] Our data do not provide the specific limitations of the drug coverage or any other benefit information, and thus our measure of plan benefits is binary. This is a limitation, as it implies that we must lump different levels of drug coverage together with each other and with all other optional benefits (e.g. eyeglasses and prosthetics) that may be correlated with it.

[19] To the extent that HMOs offer multiple products in a county, this may be a source of mismeasurement as some MCO may offer multiple plans some with drug coverage. CMS does not track M+C enrollment by managed care plan product so it is difficult to know the extent of this measurement error.

Third, we use information from CMS on the number of Medicaid enrollees by age category (65 to 74, 75 to 84, and 85 and older) and state. We proxy for the county-level Medicaid penetration rate with the state-level rate.

We gather demographic information from two sources. We use data on county per-capita income, poverty rates, population by age and race, number of practicing physicians and number of hospitals from the Area Resource File. We use detailed demographic data from the Census' Population Estimates Program in order to provide a more complete account of the entire age distribution of the elderly by county. These data provide annual county level projections of the population in each year in each county by age and sex category. The age categories that we use are 64, 65, …, 84, and 85 and older.

In some specifications, we use data from InterStudy on the county-level commercial managed care penetration rate and information on Medigap premiums from the American Association of Retired Persons (AARP), one of the largest sellers of Medigap policies. These databases are our sixth and seventh data sources.

Since drug coverage is one of the main methods in which M+C might improve health outcomes, it is useful to characterize the M+C drug coverage. The structure of the benefit varies across three dimensions: generic drug co-payments, branded drug co-payments and the total maximum drug expenditure covered by the plan. We have detailed information on the plan drug benefit structure only for 2000.

In 2000, approximately 80% of the M+C plans offered drug coverage with a mean monthly premium of $34.85. Of the plans offering drug coverage, the mean co-pay for generic prescription drugs is $7.80 (std. dev. = $2.93; median = $7), and the mean co-pay for branded prescription drugs is $16.16 (std. dev. = $6.12; median = $15). 89% of these plans cap the total

annual enrollee expenditures on drugs, with 37% setting the cap at less than $1,000 per year, and another 37% setting caps of over $3,000 per year.

It is useful to compare the prescription drug benefits to those offered through Medigap. By regulation, Medigap plan benefits fall into 10 different categories (labeled A-J). Three of these plans, H, I and J, offer drug coverage. All of these plans require a 50% co-pay on prescription drugs with Plans H and I capping the annual prescription drug expenditure at $1,250 and Plan J capping it at $3,000.[20] The cost of enrolling in a Medigap policy varies across geography and insurers. For the AARP, the mean (unweighted) monthly premium across states for plans H-J for 65 to 69 year old is $153.90, $156.57, and $192.57, respectively. Thus, M+C plans with drug benefits are significantly less expensive than Medigap plans and, in general, they offer more generous coverage.

Table 1 provides a description of the seven data sources that we use in the analysis. This table also describes the sample attrition that occurs as we merge the data together. We start out with 3,612 county-year mortality observations from the National Vitality Statistics. After merging our first five data sources together we are left with 3,597 observations; the InterStudy reduced this figure by another 110 and the addition of the Medigap premium information reduced this by another 628 observations.

Tables 2 and 3 summarize the variables used in the study. The elderly mortality rate was 5.08% during the sample period, a figure that declines by .1% over the sample, suggesting the need for time-specific controls. Cancer and heart disease make up the biggest components of mortality, accounting for about 60% of deaths. Elderly people age 75 and over are three times as

[20] Plans H and I differ in other respects. Plan I covers Medicare Part B excess charges and at-home recovery expenses while Plan H does not. Plan J offers the same benefits as Plan I with the addition of covering Medicare Part B deductible and preventive care.

likely to die as the younger elderly. Counties with some M+C plans have lower mortality rates than counties with no M+C plans; counties with some M+C plans that offer drug coverage have even lower mortality rates. This is true across all the different age-specific mortality measures. However, counties with M+C plans are different in other regards as well. For instance, they have higher incomes and are larger. To the extent that these factors do not vary over time, this suggests that fixed effects may be an important determinant of mortality. At the start of our sample, 3.3% of Medicare enrollees were enrolled in an M+C program, a figure that increased to 15.8% by the end of the sample. About 59% of M+C enrollees have prescription drug coverage, a figure that has also been increasing over time. Medicare M+C payments are about $445 per month (in constant 2000 dollars), which also has been rising over time. Counties with relatively high payment rates were more likely to have an M+C plan. There is substantial variation in the payment rate across counties — the standard deviation is 18% of the mean in 1993. Not reported in the tables, there is also substantial variation in the payment rate within a given county across time, with a within–county standard deviation of $36.7.[21] Many counties have no M+C plans, or no plans with drug coverage. For instance, by the end of our sample period, 30.7% of counties in our sample have no M+C plan with drug coverage.

Table 4 provides some evidence on the relation between the changes in the M+C payment rate and the changes in M+C enrollment and elderly mortality rates, over the period 1993 to 2000. This table is meant to give an indication of the forces that will identify the fixed effects IV estimates, as the instrumental variables estimator with one (endogenous) regressor would be the

[21] The within standard deviation is $26.3 prior to the passage of the BBA, and $15.2 afterwards. The smaller number after the BBA enactment is consistent with the fact that innovations to the payments are largely divorced from shocks in the county after the enactment. The smaller size of both of these figures relative to the overall figure suggests that the enactment of the BBA provides us with much of the variation in our instruments, and hence is a useful source of identification.

ratio of the coefficients of the differenced regressions of mortality on the instruments to the endogenous regressor on the instruments. The changes in the payment rate are broken into five quintiles. As we might expect, higher increases in the payment rate change are correlated with higher increases in the total M+C enrollment rate.[22] The trend is most pronounced between the third and fourth quintiles of the payment increase. Breaking down the enrollment change into drug and non-drug enrollment, a movement from the fourth to the fifth quintile is associated with an increase in drug enrollment, but a decrease in non-drug enrollment. In other words, a moderate increase in the payment rate between 1993 and 2000 was linked with a general increase in managed care enrollment, but a large increase in the payment rate was linked specifically with an increase in drug coverage and not with non-drug coverage.

Turning to the elderly mortality rate, in the fourth payment quintile (the payment quintile associated with an increase in non-drug HMO enrollment) there is a large increase in elderly mortality rates. However, there is an equally large decrease in mortality in the fifth quintile of the payment rates which is the quintile associated with a large increase in drug M+C enrollment. These results foreshadow our regression analysis findings and suggest that the relationship between mortality and M+C enrollment will indeed be a function of the benefits offered by the M+C plans.

V. Results

Table 5 presents the main results of the paper, estimates of the elderly mortality equation (1). The columns differ in the estimation methods and set of SES and other controls that we

[22] The quintiles for the changes in penetration rates do not sum to 3, because they all have mass points at 0, resulting from counties that had zero penetration in 1993 and 1998.

employ. Column (1), our preferred specification, provides forward mean differenced fixed effects IV estimates, as explained in Section 3.

The five fixed effects IV specifications (columns (1)-(5)) show a consistent pattern of the impact of M+C penetration on elderly mortality. We find that increased non-drug M+C penetration leads to a significant increase in mortality, while increased drug M+C penetration has no significant impact. From column (1), a ten percentage point increase in non-drug M+C enrollment (at the expense of either drug M+C or Medicare FFS enrollment) would increase the elderly mortality rate by .15 percentage points (51,000 lives), or by 2.8 percent, using the Table 2 mean mortality. Using a simplistic value of $100,000 per life year, the economic cost of these lives is approximately $5.1 billion or $1,500 per additional non-drug M+C enrollee in 2000. The 95% confidence interval for the point estimates implies that a ten percentage point increase in non-drug M+C enrollment would increase mortality by 14,400 to 86,600 deaths. The 95% confidence interval for the value of drug coverage is $428 to $2,572 per additional non-drug M+C enrollee in 2000.

Column (2) presents the standard (not forward mean differenced) fixed effects IV estimates of the parameters in order to get a sense of the potential bias from using instruments that are not strictly exogenous. The results in columns (1) and (2) are very similar suggesting that the bias from the lack of strict exogeneity is small. In the rest of the paper, we present forward mean differenced results, but the results from the standard estimator are generally very close.

Column (3) presents another robustness check. In this specification, we use the logarithm of the elderly mortality as the dependent variable and add the logarithm of the 50 to 59 year old mortality rate as a regressor. The idea is to further control for time-varying county health shocks through the mortality of this younger group. We use a log specification to allow for a

proportional increase in mortality for the older group, since the mortality rates are so different for these two groups. The sign and significance of the coefficients on managed care penetration are the same as in the base specification, and the implied magnitudes are very similar.

Column (4) adds the commercial penetration rate and the logarithm of Medigap Plan H coverage to the set of explanatory variables, while column (5) removes all the SES variables apart from age/sex categories. The coefficients and standard errors on managed care penetration for these two specifications are again very similar to the base specification.

Column (6) presents fixed effects least squares estimates of the mortality equation. This specification gives quite different results: both drug and non-drug M+C penetration are associated with roughly equal increases in mortality, with the magnitude of the coefficient on non-drug penetration being roughly one-sixth the size of the coefficient from the IV specifications.

In order to test our specification, we performed a Wu (1973) – Hausman (1978) test for the endogeneity of the regressors. We can reject the exogeneity of the M+C penetration rates, with $\chi^2(2) = 6.14$ (p=.00). We also performed a Wu (1973) – Hausman (1978) test of a fixed effects versus a random-effects IV model. We can also reject a random effects specification, with $\chi^2(63) = 1{,}203$ (p=.00). Last, we performed the LM test of overidentifying restrictions created by the fact that we have 39 instruments but only 2 endogenous regressors.[23] We fail to reject the assumption that the instruments are exogenous, with $\chi^2(37) = 28.3$ (p=.85). All three tests are based on the first column of Table 5. It is worth noting that we do not reject the LM test assumption that the instruments are exogenous for any of the five specifications, while most of the other specifications reject the Hausman test for exogeneity of the M+C penetration rates.

In Table 6, we replicate our base specification from Table 5 Column (1) for more finely defined age groups. Columns (1) and (2) partition the elderly mortality rate into the mortality rates for the 65–74 age group and the 75 and over age group. In the 75 and older age group regression, the coefficient on non-drug M+C enrollment is positive, larger than the base regression coefficient and significant. For the 65-74 age group regression, the coefficient on non-drug M+C enrollment is positive but insignificant.[24] Column (3) provides fixed effects IV estimates of the impact of the M+C penetration rates on the 50 to 59 year old mortality rate, in order to test whether there are spillovers from Medicare managed care enrollment into the non-Medicare population. We include the commercial managed care penetration rate for this regression, in order to control for the health care of this cohort. The coefficients on the M+C penetration rates have the same sign as in Table 5, are insignificant and much smaller in magnitude than the coefficients from Table 5, but are about the same magnitude as the base estimates relative to the mortality rate for this group. Thus, it is unclear from these results whether there are spillovers from the Medicare managed care market to other forms of managed care.

Columns (4) and (5) provide fixed effects IV estimates of the M+C penetration rates on disease–specific elderly mortality rates.[25] We chose the two diseases with the largest mortality for the elderly, cancer and heart disease. M+C enrollment is associated with a significantly positive increase in the heart disease mortality rate, with non-drug enrollment having approximately three times the impact of drug enrollment. The M+C non-drug coefficient on the

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[23] See Hansen (1982).
[24] In a specification with the logarithm of the 65-74 year old mortality rate as the dependent variable the coefficient on non-drug HMO enrollment is positive and significant.
[25] We do not measure the rates of death conditional on having the disease, only the death rate as determined by the cause of death.

cancer mortality specification is also positive, but small in magnitude relative to mortality and marginally significant (p-value = .05). For the most part, heart therapy drugs are administered outside of an inpatient setting and are not covered by fee-for-service Medicare. while many cancer drugs are administered in the hospital and hence covered by Medicare FFS. However, anti-nausea drugs, which may contribute to survivorship by increasing the tolerance for chemotherapy, are mostly not covered.

Explaining Our Findings

Patients enrolled in M+C plans without drug coverage are very unlikely to have any drug coverage, as alternative drug coverages generally duplicate M+C benefits. Thus, the probability that a Medicare enrollee has drug benefits moves from roughly 0% for non-drug M+C plans to 63% (in 1995) for Medicare FFS[26] to 100% for drug M+C plans. Our relative ordering of IV estimated mortality rates across groups follows this general pattern. Thus, a potential explanation for our results is that M+C drug coverage encourages the elderly to take life–extending prescription drugs and that our estimates reflect differences in the marginal cost of drugs across Medicare enrollees.

Anecdotally, physicians report that financially constrained patients "extend" their prescriptions by taking their drugs less frequently than prescribed.[27] The literature provides much data-driven supporting evidence for this explanation. In 1995, 86.6% of Medicare beneficiaries had a prescription filled, suggesting the importance of prescription drug coverage (Adams et al., 2001). Several studies (Lillard, Rogowski and Kington (1999), Davis et al. (1999) and Stuart and Grana (1998)) find a positive correlation between prescription insurance coverage and

[26] See Davis et al. (1999).
[27] See L. Lagnado, "Drug Costs Can Leave Elderly a Grim Choice: Pills or Other Needs," *Wall Street Journal*, November 11, 1999, A1.

prescription drug usage in the elderly population. Poisal and Murray (2001) estimate that Medicare enrollees without drug coverage fill 2.4 fewer prescriptions than enrollees with drug coverage. Poisal and Chulis (2000) find that among Medicare enrollees with 3 or more limitations to the activities of daily living (ADLs), those without drug coverage use 43% less prescription drugs in dollar terms than the same population with prescription drug coverage.

Other studies find this same effect within particular medical conditions. Felderman et al. (2001) find that among Medicare enrollees with coronary heart disease, those who have prescription drug coverage are more likely to use reductase inhibitors (statins), a class of relatively expensive drugs that improve the survival probability. Adams et al. (2001) and Blustein (2000) find that more generous drug coverage is associated with higher use of anti-hypertensive drugs among Medicare enrollees with hypertension.

Although suggestive of the effects that we find, none of the studies attempt to control for unobserved selection into drug coverage or managed care. In addition, these studies generally examine relatively small samples, without enough power to identify mortality differences. The increased use of drugs in the insured population can only decrease mortality if the marginal increase in drug usage is life-enhancing. However, there is some evidence on this point also. Lichtenberg (2002b) finds that increases in prescription drug usage led to reductions in lost workdays, while Lichtenberg (2002a) finds that new prescription drugs were a significant contributor to the decline in mortality over the last 30 years.

Reasonableness of the Parameter Estimates

Our estimates imply that drug coverage has a large impact on the Medicare population mortality. Given these estimated magnitudes it is appropriate to ask if these estimates are consistent with known elasticities of drug use and the impact of pharmaceutical use on mortality.

We explore the sensibility of our results with "back-of-the-envelope" calculations. Specifically, we calculate the expected change in mortality from a 10% increase in drug coverage for three common conditions: high cholesterol, hypertension and diabetes.

Our calculations use the following formula: Δ mortality = base mortality rate $\times$ (% increase in mortality from condition) $\times$ prevalence of condition in Medicare population $\times$ % Reduction in mortality from prescription drug use $\times$ % reduction in prescription drug use from lack of insurance $\times$ 10% $\times$ size of Medicare population. We use a conservative base mortality rate of 3.5%. Adams et al. (2001) report that the absence of drug coverage reduces the use of hypertension drugs for individuals with high blood pressure by 23%. We use this estimate for all three conditions, as it appears to be the roughly the median estimate from the sparse literature on compliance.

Our estimates indicate that a large impact of drug coverage among patients with high cholesterol. This condition is prevalent—50% of the elderly population has blood serum cholesterol levels in excess of 240 mg/dL (National Health and Nutrition Examination Survey III). Although Pekkanen, et al. (1990) reports that serum blood cholesterol in excess of 240 mg/dL increases mortality risk by 350% for the elderly, we use a more conservative figure of 300%. Gordon (2000) finds that pharmaceutical treatment for high blood cholesterol reduces mortality by 29%. Plugging these figures into our mortality formula yields an expected increase in mortality due to high cholesterol of 14,400 deaths from decreasing access to prescription drug coverage for 10% of the Medicare population. Performing similar calculations for hypertension and diabetes yield mortality increases of 2,800 and 3,800 lives, respectively.[28] Thus, just for these three conditions, our "back-of-the-envelope" calculations result in an expected increase of

21,000 deaths. This suggests that our estimated value of 51,000 deaths is roughly accurate, and that reasonable back-of-the-envelope calculations are well within the 95% confidence interval of 14,400 to 86,600 deaths

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Why Do Medicare Enrollees Join M+C Plans Without Drug Benefits?

Given our findings it is reasonable to ask: why do Medicare beneficiaries enroll in M+C plans without drug benefits if there is an increased likelihood of death? We offer several potential reasons. First, some enrollees may have no choice or only inconvenient choices of plans with drug coverage. In 2000, 13% of M+C enrollees in plans without drug coverage do not have any plans with drug coverage in their counties. Another likely explanation is switching costs—in 2000, 40% of the non-drug M+C enrollees are in a plan that once offered drug coverage. This may be particularly relevant for the population of ill elderly people, many of whom may have high switching costs (e.g. a son or daughter who makes enrollments decisions and assumes a caregiver role may not have time for paperwork). Last, plans may offer other benefits that might not directly impact mortality but are nonetheless valued by Medicare beneficiaries. Town and Liu (2003) and find that there is an inverse correlation between the value of the non-drug benefit offered by the plan and the likelihood they offer drug benefits. Consistent with this relationship, McBride (1998) finds an inverted U-shape relationship between the payment rate and the provision of non-drug benefits by M+C plans.

VI. Conclusions

This study examines the impact the Medicare managed care program Medicare+Choice on the elderly mortality rate. We model two separate managed care penetration rates, the percent

[28] The inputs into the mortality formula for hypertension and diabetes are available from the authors upon request.

of elderly people covered by an M+C plan with prescription drug coverage, and the percent covered by a plan with no prescription drug coverage. We use a fixed effects IV specification. The fixed effects imply that we are examining changes in mortality over the 1993–2000 sample period within a county. We use IV to control for the fact that changes in the enrollment into managed care over the sample period are endogenous. The instruments are functions of the M+C payment rate, which is based on the mean of the 3– to 8–year lagged costs in the county. As we control for fixed effects, time–varying SES and other health coverages, these instruments appear to be reasonable.

We find that an increase in M+C non-drug enrollment significantly increases mortality while an increase in M+C drug enrollment has no significant impact relative to FFS coverage. A probable explanation is that drug benefits causes Medicare enrollees to use more drugs which extends their lives, although it is possible that the impact is caused by other benefits that are correlated with drug coverage.

Our results suggest several policy implications. First, that managed care with drug benefits provides care (at least as measured by mortality) that is as good as what the mean enrollee in the fee-for-service sector receives for those who select those plans. Second, that policies that encourage M+C plans to offer drug benefits will likely reduce mortality rates. Using a value per life-year of $100,000, each enrollee removed from a non-drug M+C plan is worth $1,500. Third, that there are significant mortality benefits to providing prescription drug coverage. Last, that the rise of managed care during the 1990s likely did not result in a deterioration of the quality of health care in terms of mortality.

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Table 1:
Mortality Data Table

Data Set	Source	Variables	Number of matched observations
Multiple Cause of Death Data	National Center for Health Statistics — National Vitality Statistics	Mortality rates by age and cause of death	3,612
State-County-Plan Penetration file and M+C/AAPCC Standardized Per Capita Rates of Payment	Center for Medicare and Medicaid Services	M+C enrollments by HMO benefit structure and CMS payment data	3,612
Medicaid Program Statistics	Center for Medicare and Medicaid Services	Medicaid enrollments by age classification	3,612
Area Resource File	Area Resource File	Population by race, poverty rates, per-capita income, number of MDs and hospitals.	3,612
Population Estimates Program	Bureau of the Census	Predicted population by age and sex categories	3,597
InterStudy	InterStudy	Commercial HMO enrollment	3,487
Medigap Premium	AARP	Medigap Premiums for Plan H	2,859

Table 2:

Summary statistics by county and year

Variable	Entire sample	1993	2000	2000 subsample where M+C HMO drug penetration rate: = 0	2000 subsample where M+C HMO drug penetration rate: >0	2000 subsample where M+C non-drug penetration rate: = 0	2000 subsample where M+C non-drug penetration rate: >0
65 and over mortality rate (%)	5.08 (.52)	5.16 (.45)	5.04 (.56)	5.20 (.52)	4.96 (.57)	4.99 (.60)	5.16 (.44)
Mortality rate 65-74 (%)	2.53 (.38)	2.64 (.35)	2.41 (.39)	2.53 (.40)	2.35 (.36)	2.42 (.41)	2.39 (.32)
75 and over mortality rate (%)	8.25 (.76)	8.58 (.65)	8.16 (.73)	8.35 (.65)	8.05 (.74)	8.10 (.79)	8.26 (.55)
Mortality rate for heart disease (%)	1.73 (.28)	1.83 (.27)	1.64 (.27)	1.62 (.24)	1.64 (.28)	1.61 (.26)	1.70 (.27)
Mortality rate for cancer (%)	1.00 (.18)	1.15 (.11)	1.11 (.12)	1.14 (.13)	1.13 (.12)	1.11 (.13)	1.11 (.10)
1000 × MDs per capita	2.5 (1.8)	2.3 (1.6)	2.6 (1.8)	2.6 (1.9)	2.6 (1.7)	2.6 (1.8)	2.6 (1.5)
1000 × Hospital beds per capita	3.4 (2.1)	3.9 (2.3)	3.0 (1.9)	3.8 (2.0)	2.6 (1.8)	3.1 (2.1)	2.8 (1.5)
Percent elderly	12.5 (3.9)	12.4 (3.6)	12.5 (3.8)	12.0 (2.4)	12.8 (4.3)	12.4 (4.2)	12.8 (2.8)

Note: each cell provides the mean value with the standard deviation below in parentheses.

Table 3:
More summary statistics by county and year

Variable	Entire sample	1993	2000	2000 subsample where M+C HMO drug penetration rate: = 0	2000 subsample where M+C HMO drug penetration rate: >0	2000 Subsample where M+C non-drug penetration rate: = 0	2000 Subsample where M+C non-drug penetration rate: >0
M+C drug penetration rate (%)	7.2 (120)	1.4 (5.1)	11.9 (14.9)	0	18.1 (15.0)	13.6 (16.2)	8.1 (10.6)
M+C drug penetration rate = 0 (%)	49.0 (50.0)	80.3 (40.0)	34.6 (47.6)	100	0	37.6 (48.5)	28.1 (45.0)
M+C non-drug penetration rate (%)	3.7 (7.8)	1.9 (5.1)	3.9 (8.5)	3.7 (8.9)	4.0 (8.4)	0	12.1 (11.4)
M+C non-drug penetration rate = 0 (%)	59.8 (49.0)	65.5 (47.5)	68.1 (46.7)	74.5 (43.9)	64.9 (47.8)	100	0
M+C monthly payment rate	$445 ($84)	$398 ($70)	$497 ($72)	$450 (44.6)	$522 (72.1)	$497 (76.2)	$497 (64.0)
Income (thousands)	$25.2 (6.7)	$20.9 (4.5)	$29.7 (7.8)	$26.4 (4.4)	$31.5 (8.6)	$29.2 (7.8)	$30.7 (7.8)
Unemployment rate (%)	5.0 (2.7)	6.5 (2.2)	3.9 (2.4)	3.9 (1.6)	4.0 (2.8)	3.9 (2.6)	4.0 (2.0)
Total population (thousands)	422 (626)	455 (766)	442 (654)	223 (158)	557 (776)	436 (707)	454 (527)
N	3,612	409	457	158	299	311	146

Note: each cell provides the mean value with the standard deviation below in parentheses.

Table 4:

Changes in payment rate, mortality, and M+C enrollment, 1993-2000

Quintile and range of change in payment rate:	Percentage point change in total M+C enrollment	Percentage point change in M+C non-drug enrollment	Percentage point change in M+C drug enrollment	Percentage point change in elderly mortality
1 [$40 – $80]	-1.3	-.89	-.40	.016
2 [$81 – $95]	-.16	.11	-.26	.019
3 [$96 – $107]	-.47	.0075	-.47	-.030
4 [$108 – $124]	.20	1.1	-.93	.050
5 [$125 – $216]	1.8	-.0036	2.1	-.055

Note: Each cell provides the mean of the given variable with the year means removed, given that the change in the M+C payment rate is in the specified quintile.

Table 5:

Elderly (65 and over) mortality rate on M+C penetration rates

Dependent variable	65 and over mortality rate (1)	65 and over mortality rate (2)	Log 65 and over mortality rate (3)	65 and Over Mortality Rate (4)	65 and Over Mortality Rate (5)	65 and Over Mortality Rate (6)
Estimation method	Forward mean differenced FE IV	Standard fixed effects IV	Forward mean differenced FE IV	Forward mean differenced FE IV	Forward mean differenced FE IV	Fixed effects least-squares
M+C drug penetration rate	.00062 (.0020)	-.0021 (.0016)	.010 (.039)	.0013 (.0023)	-.000086 (.0019)	.00097 (.00064)
M+C non-drug penetration rate	.015** (.0051)	.015** (.0049)	.31** (.098)	.015* (.0060)	.011* (.0055)	.0023** (.00078)
Log of Mortality Rate 50 to 59 year olds	—	—	-.000034 (.000019)	—	—	—
Commercial HMO penetration rate	—	—	—	.00043 (.00047)	—	—
Log of Medigap Premium	—	—	—	-.00047 (.00061)	—	—
Other regressors included	Percent elderly in Medicaid; percent of population 65 and over; percent of population in poverty; log per capita income; unemployment rate; MDs and hospital beds per capita; percent white, black and Hispanic; all regressors from (5)				Year dummies; percent elderly at each age/sex cell	Same as (1) – (4)
N	3,597	3,597	3,597	2,857	3,597	3,597 R^2(within)=.23

*Significant at the 5% level
** Significant at the 1% level

Table 6:

Mortality rates for different age categories and specific diseases on M+C penetration rates

Dependent variable	75 and over mortality rate (1)	65 to 74 mortality rate (2)	50 to 59 mortality rate (3)	65 and over heart disease mortality rate (4)	65 and over cancer mortality rate (5)
Estimation method	Forward mean differenced FE IV	Forward mean differenced FE IV	Forward mean differenced FE IV	Forward mean differenced FE IV	Forward mean differenced FE IV
M+C drug penetration rate	.0022 (.0037)	-.00018 (.0013)	-.00095 (.00055)	.0032** (.0013)	-.0011 (.00063)
M+C non-drug penetration rate	.025** (.0096)	.0054 (.0032)	.0022 (.0014)	.0093** (.0035)	.0034* (.0017)
Commercial HMO penetration rate	—	—	-.000056 (.00013)	—	—
Percent of population 65 and over	-.22** (.043)	-.096** (.013)	—	-.035** (.011)	-.029** (.0064)
Other regressors included	Percent population in Medicaid for age range; percent of population 65 and over; percent of population in poverty; log per capita income; unemployment rate; MDs and hospital beds per capita; percent white, black and Hispanic; year dummies; percent at each age/sex cell for all included ages				
N	3,597	3,597	3,460	3,597	3,597

*Significant at the 5% level
** Significant at the 1% level

Appendix

First-stage regression results
(standard errors in parentheses)

Instruments	M+C with Drug Coverage Share			M+C without Drug Coverage Share		
	t+1	t	t-1	t+1	t	t-1
Payment rate	-.00019 (.00036)	.0031 (.00047)	-.0022 (.00042)	.0012 (.00031)	-.0014 (.00041)	-.000001 (.00036)
(Payment rate/1000)^2	-.67 (1.54)	.26 (1.89)	-.27 (.15)	1.08 (1.32)	.49 (1.62)	.80 (1.31)
(Payment rate/1000)^3	3.14 (3.92)	-9.21 (3.50)	6.81 (2.81)	-4.92 (3.38)	8.79 (3.02)	-4.12 (2.42)
(Payment rate/1000)^4	-10.68 (10.54)	24.30 (11.87)	-2.06 (9.31)	12.59 (9.07)	-25.33 (10.22)	6.59 (8.01)
Ln Payment rate	-.063 (.16)	-1.31 (.21)	1.07 (.17)	-.51 (.14)	.57 (.18)	.024 (.15)
(Ln Payment rate)^2	.055 (.29)	.62 (.35)	.95 (.28)	-.43 (.25)	.41 (.30)	-.000065 (.24)
2nd payment quintile	.0021 (.0046)	-.0048 (.0046)	-.013 (.0047)	-.0024 (.0040)	.0030 (.0040)	.0031 (.0040)
3rd payment quintile	.011 (.0072)	.000076 (.0073)	-.014 (.0072)	-.0020 (.0063)	.0011 (.0063)	.0049 (.0063)
4th payment quintile	.0054 (.010)	-.00034 (.010)	-.012 (.013)	-.00025 (.0087)	.0038 (.0086)	.0049 (.0087)
5th payment quintile	.0077 (.013)	.0036 (.013)	-.0021 (.013)	-.0017 (.011)	.0027 (.011)	.0013 (.0011)
Mean payment of MSA counties	-.00022 (.00017)	-.000013 (.00023)	.0028 (.0018)	-.000031 (.00015)	.00011 (.00020)	-.00015 (.00016)
Minimum payment of MSA counties	.000088 (.00010)	.000015 (.00013)	-.00011 (.00011)	-.000035 (.000088)	-.000061 (.00012)	.00012 (.00093)
Maximum payment of MSA counties	.00086 (.00089)	.000057 (.00011)	-.00016 (.000095)	-.0000089 (.000076)	-.000018 (.00010)	.000049 (.000082)
Partial R^2 of Instruments F-test (p-value)		.10 11.1 (.00)			.024 2.20 (.00)	

Note: Regressions include all of the exogenous variables.